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## Long term dry cargo freight rates forecasting by using recurrent fuzzy neural networks

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### Abstract

Maritime transport rates are very important for planning economic strategies. Various methods have been applied to seaborne trade forecasting. This study presents a genetic algorithm based trained recurrent fuzzy neural network for long term dry cargo freight rates forecasting. The empirical results show that proposed work has better accuracy than the other approaches which have used the same data set.

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**Keywords:** Forecasting; genetic algorithm; recurrent fuzzy neural networks

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### 1. Introduction

Governmental and non-governmental entities use historical data to forecast the future trends that can help them in their decision making process. The maritime transport is an essential part of the global economic system. Around 80 percent of the volume of international trade in goods is carried by sea<sup>20</sup>. Therefore the maritime freight rates forecasting is very important to the success of policy decisions. The interaction between demand and the supply of maritime transport services determines the freight rates. There are political, environmental and economic factors affecting supply and demand that expose the freight rates.

Seaborne trade is classified as bulk or general cargo<sup>26</sup>. Bulk cargo is commodity cargo that is transported unpackaged in large quantities. The dry bulk categorized either as major bulk (iron ore, coal, grain, bauxite/alumina

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and phosphate rock) or minor bulk (agricultural products, mineral cargoes, cement, forest products and steel products)<sup>20</sup>.

The earliest studies of economic research of the shipping business were published in the decades following World War I. Baltic Exchange maintains a number of indices on the shipping freight market the most important of which is the Baltic Exchange Dry Index (BDI)<sup>27</sup>. BDI is a daily index that takes into consideration 26 shipping routes measured on a time-charter and voyage basis. Long term freight rate index (LFI) presented by Duru and Yoshida<sup>10</sup> based on combination of 15 different series of dry cargo freight rate.

Several methods are used in literature for the maritime freights rates forecasting. Cullinane<sup>8</sup> used ARIMA for the forecasting of freight rates. Kavussanos<sup>16,17</sup> used ARCH to model the time-varying volatility for dry bulk. Cullinane et al.<sup>9</sup> used ARIMA to forecast BDI index. Batchelor<sup>6</sup> used ARIMA, VAR, VECM, and S-VECM to forecast the rates of Panamax carriers. Zeng and Qu<sup>25</sup> used improved empirical mode decomposition to investigate the volatility of the BDI and for the BDI forecasting. Duru and Yoshida<sup>11</sup> applied classical DELPHI for short term BDI forecasting. Duru et al.<sup>14</sup>, proposed a fuzzy-DELPHI adjustment process to the dry bulk shipping index forecasting. Duru<sup>13</sup> suggested fuzzy integrated logical forecasting (FILF) and its extended version (E-FILF) and applied these approaches to BDI. Duru<sup>15</sup> proposes an improvement on the FILF by multivariate modeling. Duru et al.<sup>12</sup>, proposed a first order bivariate fuzzy time series (BiFITS) and compared the results with other approaches (Chen<sup>7</sup>, Naïve I, ARIMA, Holt-Winters) to give the best method for LFI forecasting. Lin and Wang<sup>14</sup> propose fuzzy set theory and grey system for modeling the prediction of BDI, and employ the ARIMA model for the calibration of the data structure to depict the trend.

Fuzzy neural networks (FNN) can process both numerical and perception based information<sup>1</sup>. There are two approaches for training FNN. First approach is application of level-sets of fuzzy numbers and application of the back-propagation (BP) learning algorithm. The second approach to learning of regular and FNN involves evolutionary algorithms (EA) to minimize error function and determine fuzzy connection weights and biases<sup>5</sup>. In case of dynamic or temporal problems of the existing FNN based on the feed-forward architecture there is a need for recurrent fuzzy neural network (RFNN). Various EA based learning algorithms for RFNN with fuzzy inputs, fuzzy weights and biases, and fuzzy outputs have been developed<sup>2,3,4,18, 21,22,23,24</sup>.

This paper presents genetic algorithm (GA) based trained RFNN for long term dry cargo freight rates forecasting. The evaluation process is carried out by means of the same data set which is used by Duru et al.<sup>12</sup>. The rest of this paper is organized as follows: Section 2 describes the methodology, Section 3 presents the empirical results, and the last section contains some concluding remarks.

## 2. Methodology

### 2.1. Recurrent fuzzy neural network (RFNN)

The structure of the RFNN that is used in this work is presented in Fig.1, and the GA based training process is schematically shown in Fig.2<sup>2,3,4,5,21,22,23,24</sup>. In this work a three layer GA based trained RFNN to forecast the long term dry cargo freight rates. The RFNN has three input neurons at layer 0, twelve hidden neurons at layer 1 and one output neuron at layer 2. A total of 10000 iterations in trained RFNN are sufficient in this study to guarantee convergence of the weights obtained.

### 2.2. Dataset

This study used the RFNN to forecast the Long term freight rate index (LFI), which is presented by Duru and Yoshida<sup>10,12</sup>. The data are annually for the period 1741 to 2008, giving a total of 268 observations.

### 2.3. Evaluation criteria

In this study, mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE) and normalized root mean square error (NRMSE) given by Eqs. (1), (2), (3), and (4) respectively are used as the indexes of forecasting accuracy.



They are defined as follows:

$$MAE = \frac{1}{N} \sum_{i=1}^N |Y_i - P_i| \quad (1)$$

$$MAPE = \left( \frac{1}{N} \sum_{i=1}^N \frac{|Y_i - P_i|}{Y_i} \right) \times 100\% \quad (2)$$

$$RMSE = \sqrt{\left( \frac{1}{N} \sum_{i=1}^N (Y_i - P_i)^2 \right)} \quad (3)$$

$$NRMSE = \frac{RMSE}{Y_{\max} - Y_{\min}} \quad (4)$$

where  $Y_i$  is actual value and  $P_i$  is forecasted value of the  $i^{\text{th}}$  data obtained,  $Y_{\max}$  is maximum actual value,  $Y_{\min}$  is minimum actual value, and  $N$  is the number of data.

#### 2.4. Experimental procedure

In this work the forecasting model relationship assumed as:

$$y(k) = F(y(k-3), y(k-2), y(k-1)) \quad (5)$$

where  $y(k)$  is the freight rate of the  $k^{\text{th}}$  year,  $y(k-1)$  is the freight rate of the  $(k-1)^{\text{th}}$  year,  $y(k-2)$  is the freight rate of the  $(k-2)^{\text{th}}$  year and  $y(k-3)$  is the freight rate of the  $(k-3)^{\text{th}}$  year.

### 3. Empirical results

In this section we consider the forecasting results of the long term dry cargo freight rates. The results of implementing the RFNN were obtained using i5 CPU PC with 8GB of RAM, Ubuntu OS and Java.

Actual and forecasted annually LFI values are given in Fig.3. Table 1 show comparative results obtained by different methods given by Duru and Yoshida<sup>12</sup> and the proposed approach based on RMSE, MAE, MAPE and NRMSE.

Table 1. RMSE, MAE, MAPE and NRMSE results

	Näive I*	Chen*	BiFITS*	ARIMA(2,1, 3)*	Holt-Winters*	RFNN
RMSE	107.1	101.24	82.41	99.30	112.24	36.09
MAE	39.51	41.55	36.62	50.06	43.85	24.9
MAPE	15	17	16	20	16	14.96
NRMSE	0.0492	0.0467	0.0421	0.0433	0.0489	0.0157

\*Duru et al.<sup>12</sup>

### 4. Conclusions

In this work a genetic algorithm based trained recurrent neural network used for long term freight rate index forecasting. From the experimental results, we concluded that the recurrent neural networks gave better accuracy performance than other approaches regarding to mean absolute error, mean absolute percentage error, root mean square error and normalized root mean square error evaluation.

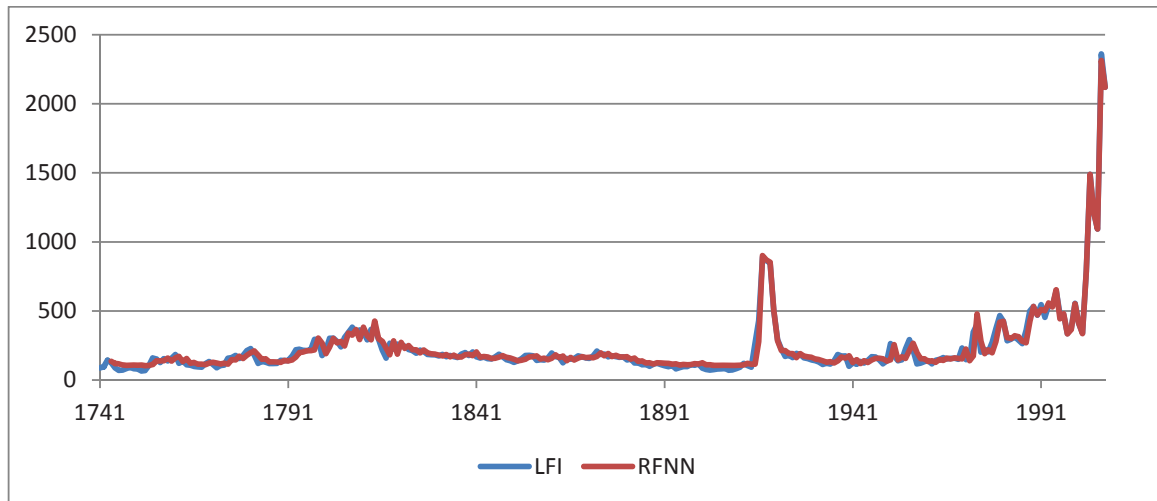


Fig. 3. The actual and forecasted values

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